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EMPLOYEE ATTRITION PREDICTION IN INDUSTRY USING MACHINE LEARNING TECHNIQUES

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ABSTRACT

Companies are always looking for ways to keep their professional personnel on board in order to save money on hiring and training. Predicting whether or not a specific employee would depart will assist the organisation in making proactive decisions. Human resource problems, unlike physical systems, cannot be defined by a scientific-analytical formula. As a result, machine learning approaches are the most effective instruments for achieving this goal. In this study, a feature selection strategy based on a Machine Learning Classifier is proposed to improve classification accuracy, precision, and True Positive Rate while lowering error rates such as False Positive Rate and Miss Rate. Different feature selection techniques, such as Information Gain, Gain Ratio, Chi-Square, Correlation-based, and Fisher Exact test, are analysed with six Machine Learning classifiers, such as Artificial Neural Network, Support Vector Machine, Gradient Boosting Tree, Bagging, Random Forest, and Decision Tree, for the proposed approach. In this study, combining Chi-Square feature selection with a Gradient Boosting Tree classifier improves employee attrition classification accuracy while lowering error rates.

Key words: Feature Selection, Employee Attrition, Classification, Error Rates, Accuracy.

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1. INTRODUCTION

Employee turnover is another name for employee attrition. Wearing down is a common problem, and it's more prevalent in today's industry. In the vast majority of associations, it is

one of the most important difficulties [1]. Employee Defection refers to the gradual reduction in the number of representatives due to retirement, renunciation, or death. Wearing down rates vary widely from industry to industry in terms of their own principles, and these rates can also differ between bright and inept positions. Organizations face a daunting task of enrolment and gift retention, while also dealing with ability misfortune due to continual loss, whether because to industry midtowns or willful person turnover [2]. When a well-trained and well-adjusted employee quits the company, a void is created. As a result, the organisation loses important skills, information, and business relationships [29]. Current chiefs and individual executives are extremely interested in reducing wear and tear in the organisation in such a way that it will contribute to the organization's most extreme viable development and progress. Any business's representative consent is, in any case, organisation. If the situation is not handled properly, critical personnel departures can result in a significant loss of earnings. Representative turnover results in execution losses, which can have a long-term negative influence on businesses [3][4]. With rate reduction a significant concern for every industry, businesses endeavour to use innovative business methods to reduce maintenance [5]. Although there is no way to completely eliminate continuous loss, we can reduce it by implementing appropriate solutions. It could also be when a supervisor estimates the rate of employee turnover ahead of time [30].

Machine learning can be used to create labelled data classifications or to create hidden structures from unlabeled data. The ability of machine learning algorithms to anticipate the possibility of a person leaving an organisation can be used by top-level management of firms [6][7]. This procedure will aid in the control of attrition-causing causes and the prevention of attrition. Employee turnover is a significant issue for employers. Every organization's ability to retain talent is critical. As a result, if management can obtain a prediction likelihood of employee separation as well as the variables driving the separation, it can be useful in making actions that reduce attrition risk [8] [9]. Here's when machine learning comes in handy. Top management will take proactive actions to retain personnel based on the forecasts made by machine learning algorithms [10].

2. RELATED WORKS

Tang, Ziyuan, Gautam Srivastava, and Shuai Liu [11] based on accounting market big data, offered a strategy for selecting accounting models for small and medium-sized firms (SMEs) (AMBD). To begin, some indicators from a company's solvency, operating capacity, profitability, and growth capacity are chosen, such as the current ratio, quick ratio, asset-liability ratio, accounts receivable turnover rate, and other indicators from the solvency, operating capacity, profitability, and growth capacity. Following that, the AMBD constraints are classified using the principal component analysis method. Finally, the optimal accounting model is established by iteration by combining particle swarm optimization with ant colony optimization.

Marichelvam, M. K., M. Geetha, and OmurTosun [12] the effect of human variables was taken into account when solving the multi-stage hybrid flow shop scheduling problem with identical parallel machines at each level. The aim function is to minimise the weighted sum of the make span and total flow time. Because the problem is NP-hard, we propose an improved version of the particle swarm optimization (PSO) algorithm to solve it. To improve the PSO algorithm's initial solutions, a dispatching rule and a constructive heuristic are used. The variable neighbourhood search (VNS) algorithm is used with the PSO algorithm to provide the best results in the shortest amount of time.

Jhaver, Mehul, Yogesh Gupta, and Amit Kumar Mishra [13] the study's unique addition is to investigate the usage of the Gradient Boosting technique, which is more resilient due to its regularisation formulation. Gradient Boosting is compared to three commonly used supervised

classifiers, such as Logistic Regression, Support Vector Machine, and Random Forest, using worldwide retailer data to show that it has a higher accuracy for forecasting staff turnover.

Machado, Marcos Roberto, Salma Karray, and IvaldoTributino de Sousa [14] showcased a financial company's deployment of a Machine Learning model to predict customer loyalty. The researchers assessed the accuracy of two Gradient Boosting Decision Tree Models: XGBoosting and the LightGBM algorithm, which has never been used to predict customer loyalty.

Keshri, Rajat, and Srividya [15] Microsoft published the LightGBM algorithm in 2017, which was explored. The authors compared LighGBM to other known algorithms in this paper. The dataset's data is used to compare LightGBM to other classification algorithms and demonstrate LightGBM's excellent prediction accuracy.

Padmasini, Ms, and K. Shyamala [16] A model is presented that clusters Original Equipment Customers, Distributors, and Dealers in order to determine what the consumer thinks about the products and firm based on pricing, quality, and delivery logistics, and then decides to buy an automobile product and become a loyal client. The Integrated Gower based PSO-KMode model proposes using the Gower dissimilarity measure and optimising the data using Particle Swarm Optimization with K Modes clustering method to locate the existing consumer through a survey.

Eitle, Verena, and Peter Buxmann [17] proposed a model to assist software sales reps in managing the complicated sales funnel. Data-driven qualification assistance decreases the high degree of arbitrariness produced by professional expertise and experiences by incorporating business analytics in the form of machine learning into lead and opportunity management. Using real business data from the company's CRM system, the authors created an artefact consisting of three models to map the end-to-end sales pipeline.

3. PROPOSED FRAMEWORK FOR EMPLOYEE ATTRITION PREDICTION

3.1. Artificial Neural Network Classifier

The organic neuron employed for prediction formed the basis for Neural Network [18]. Network of Neurons Let's see if we can get a single neuron to learn. Figure 1 depicts a single neuron with a single input. Where O is the output, σ is the sigmoid function, ξ is the neuron's input, and ω is the weight that connects the input to the neuron, the provided equation defines the single input neuron.

$$O = \sigma(\xi\ \omega)$$

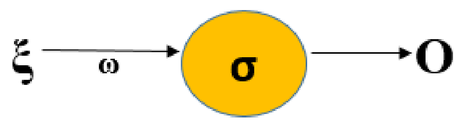

Figure 1 Single input neuron0

When a neuron has many inputs, as shown in Figure 2, the MLP is made up of inputs that are weighted and connected to the layer. The neuron then takes many inputs and forms a multilayer perceptron as a result. The diagram depicts a multi-layer experience.

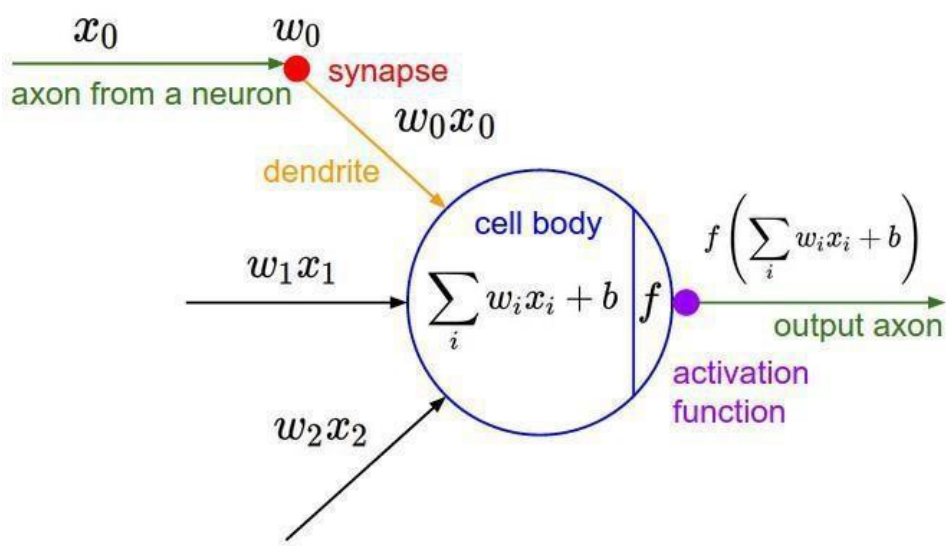

Figure 2 Multilayer perceptron

$$O = (\xi 1\omega 1 + \xi 2\omega 2 + \cdots \ldots\ldots + \xi k\omega k) + \Theta$$

where O is the output.

σ is the sigmoid function or transformed function.

ξ is the input to the neuron.

ω is the weight of input (1 to k).

Θ is the bias.

3.2. Support Vector Machine Classifier

A support vector machine that separates hyperplanes is described. An ideal hyperplane that categorises new instances is the approach performance. In a two-dimensional environment, this modern hyper plane divides a plane into two halves, with each class on one side. It produces better outcomes when dealing with categorization problems that are more complex. Each function that represents the coordination of the plane as a point in n-dimension is assigned a value to each data element. The SVM [19] is a highly effective categorizer that separates both groups.

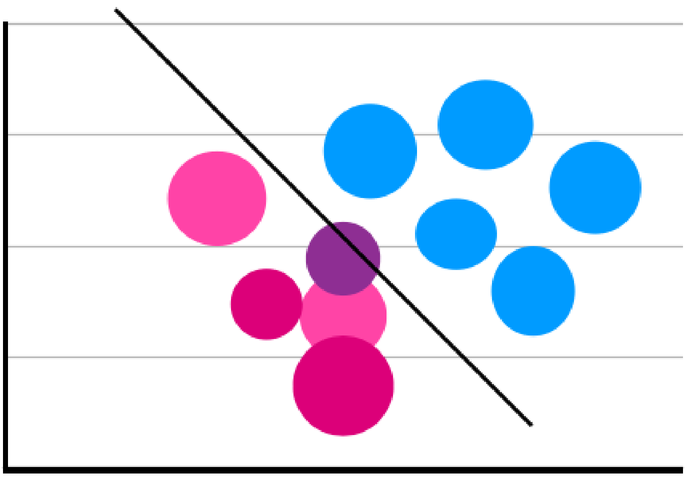

Figure 3 Support Vector Machine Hyper plane classifying two classes

3.3. Gradient Boosting Classifier

Gradient boosting (GB) builds new models sequentially from a set of weak models by minimising loss functions for each new model. The descent of gradients determines the loss function. Every new model that uses the loss function better matches the observations and improves overall accuracy. Boosting, on the other hand, must be stopped at some point; otherwise, the model looks to be overfishing. The stop criterion could be a certain level of accuracy or a certain number of models.

The GBDT [20] community model of sequence-trained decision-making trees is a community model of sequence-trained decision-making trees. GBDT adapts negative gradients to train decision trees in any iteration (also called residual failures). Learning decision bodies is the most time-consuming component of learning a decision tree in GBDT, and identifying the appropriate split points is the most time-consuming aspect of learning a decision tree. The pre-sort algorithm, which lists all possible dividing points with pre-sorting function values, is one of the most used dividing dots. This method is simple and can find the best splits, however it is unsuccessful in terms of training speeds and memory usage.

3.4. Bagging Classifier

Bagging methods are a powerful category of algorithms that combine many cases of black box estimators in random subsets of the original data set, then aggregate their predictions effectively to work out and construct the final prediction. The storage methods go to great lengths to incorporate randomization into their creation in order to reduce differences across the basic estimators. Consider a scenario in which you have a learner for scenario The Decision Tree. You've probably tried to improve the accuracy and variance of Bootstrap technology.

- Using a next scheme technique, you can generate numerous samples of your data set that are classified as a training set: you can randomly imagine every variable in your training set and then pull it back. As a result, some of the training elements in the new sample are present several times, while others are missing unintentionally. The samples must be identical in size to the train package.
- You can instruct your pupil to attain efficient results and refine the model on each produced sample.
- If students regress, you use the procedure to estimate the average number of students, or to vote if they are graded.

3.4. Random Forest Classifier

Random Forest is a master learning technique used for grading and regression. It's a kind of ensemble technique that combines a bunch of weak models to create a powerful model. The random forest generates several tresses. Voting for that class should be used to categorise each tree. This is a categorization. The forest chooses the classification with the most votes. Figure 3.4 depicts the random forest selection approach [22].

Take the test to evaluate the features and choose trees in order to predict and save the findings.

- Determine the votes for each projected outcome.
- Assume that the forecast with the most votes is the final forecast.

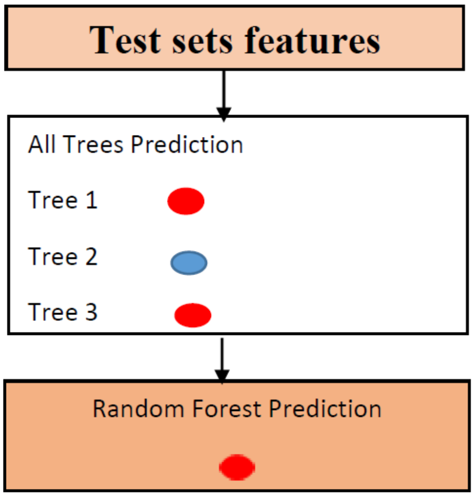

Figure 4 Prediction process taken by random forest

3.6. Decision Tree Classifier

The decision tree algorithm [23] is a supervised research method for classification and regression problems. Its main purpose is to create a training model that may be used to anticipate employee attrition decisions using data sets from previous studies. It attempts to tackle the problem through the use of nodes or node hierarchies. Three nodes are present:

- Root
- Internal Nodes
- Leaf Nodes

The root node represents the complete sample, which is then separated into leaf nodes that display the attribute divided into leaf nodes that represent the class Labels.

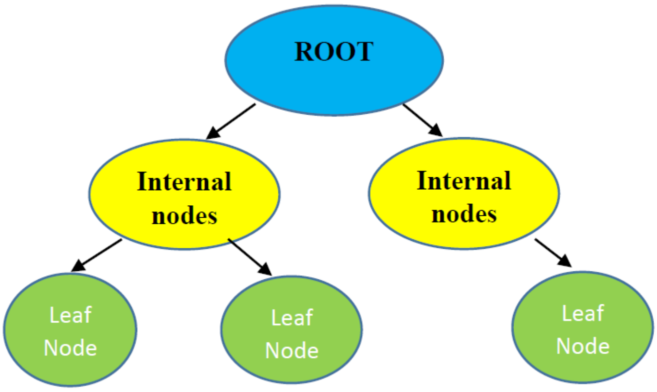

Figure 5 Representation of the Decision Tree

3.7. Proposed Research Methodology with Feature Selection Technique

A feature selection algorithm is given in this research paper based on Chi-Square in order to predict employee attrition using algorithms for machine learning. The comparison of other functional approaches for the classification of employee attrition is often compared with the Chi-Square. The methods for selecting features such as correlation-based role selection, the gain ratio, chi-square-based feature selection, the Fishers Exact Test are used to predict Employee Attrition.

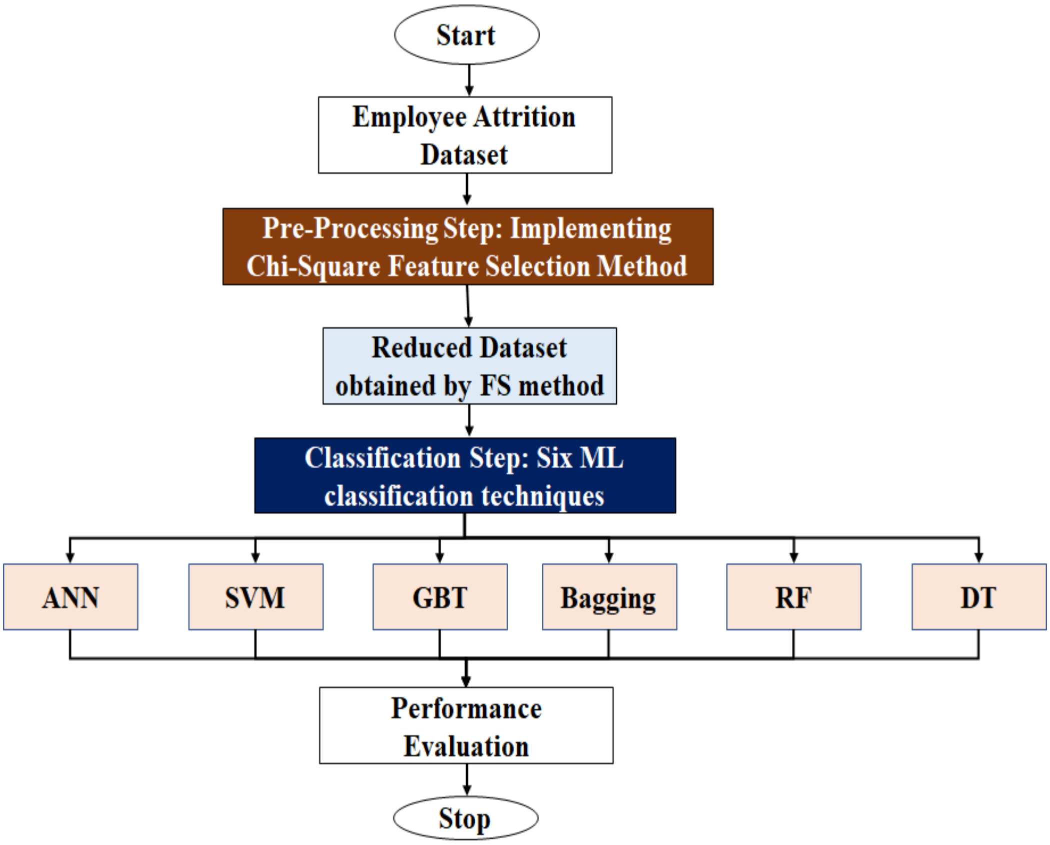

Figure 6 Proposed Research Methodology for Predicting Employee Attrition in Industry

3.7.1. Correlation based Feature Selection

The relationship between all features and the output class is determined in this algorithm, and the heuristic correlation assessment function is utilised to choose the best feature subset [24]. It examines the relationship between nominal and category features, with numerical features being represented by discrete values. The equation must be used to choose the correlation function.

$$r_{zc} = \frac{K\overline{r_{zi}}}{\sqrt{K + K(K-1)\overline{r_{ii}}}}$$

Where r_{zc} denotes the relationship between features and class variable, K represents the number of features, $\overline{r_{zi}}$indicates the mean value of correlated feature-classes and $\overline{r_{ii}}$represents the mean value of inter-correlated features.

3.7.2. Information gain Ratio Feature Selection

Knowledge determines the amount of data received by a term in a text for class prediction. Gaining knowledge In relation to the development of a subgroup on the class attribute, it determines the relevant information value. Data speculation indexes are frequently used to evaluate attributes. The final goal of this research is to provide an undesired range of data gain or to calculate the entropy value for every data [25]. It's a supervised, univariate, simple, solid, symmetrical, and entropy-based feature selection approach. For the functions X and Y, the following information is provided:

$$Informationgain(X,Y) = H(X) - H(X \mid Y)$$

Where H(X), H (X|Y) is calculated on X and Y for entropy values. X entropy can be computed as

$$H(X) = -\sum_i P(x_i)\log_2(P(x_i))$$

X|Y entropy calculation is shown below:

$$H(X \mid Y) = -\sum_j P(y_j)\sum_i P(x_i \mid y_j)\log_2(P(x_i \mid y_j))$$

Similarly, this strategy analyses the ratio for each characteristic independently and chooses 'm' as the most appropriate function, i.e. it considers the most significant function F with a high information gain as the most relevant function. The fundamental disadvantage of this technique is that it selects a high-data-gain attribute that may or may not be more informative. Because the characteristics are chosen globally, knowledge acquisition is unable to handle redundant features.

3.7.3. Gain Ratio Feature Selection

The revised information gain version is the Gain Ratio. It takes into account daughter nodes, which are nodes in which an attribute separates the class data. This limits the appreciation for the fact that the process of acquiring information has four characteristics and great potential values [26]. Equation provides a benefit ratio.

$$GainRatio = \frac{InformationGain}{H(X)}$$

We normalise information gain by breaking it into X entropy when forecasting variable Y, and vice versa. The gain ratio now has a value between 0 and 1 as a result of this normalisation. When the gain ratio is 1, it signifies that X information completely predicts Y, and there is no relationship between Y and X. It favours variables with lower value as compared to information gain.

3.7.4. Chi-Square Feature Selection Method

The observed and predicted frequency are two parameters in Chi-Square feature choices [27]. The qualities' weights can also be discovered. The greatest weight attributes are those that match to the relevant attributes. This method examines the label of the class. This is where the predictor's variable is chosen. This attribute value with the class numbers 'r' and 'c' is defined as

$$x^2 = \sum_{i=1}^{r}\sum_{j=1}^{c}\frac{(O_{ij} - E_{ij})^2}{E_{ij}}$$

Where O_{ij} is the number of ‘i’ value occurrences in class ‘j’. E_{ij} is the number of events predictable with the value ‘i’ and the class ‘j’.

3.7.5. Fisher's Exact Test

Using a well-known fisherman ratio concept and a heuristic approach to establish a value for qualities, the Fisher score can be used to choose the suitable attributes [27]. The revenue is

- Define the features applicable to any particular issue.
- Reduces issue size and storage in your machine.
- Minimize calculation time to increase prediction accuracy as well.
- Strengthen the classification by eliminating irrelevant characteristics and noise.

4. RESULT AND DISCUSSION

4.1. Description of the Dataset

The employee attrition dataset is considered to evaluate the performance of the proposed framework with various feature selection and classifiers. The employee attrition dataset is taken from Kaggle repository [28]. The following table 1 represents the dataset used in this research work.

Table 1 IBM Employee Attrition Dataset

Sl.No	Feature Name
1	Age
2	Attrition
3	Business Travel
4	Daily Rate
5	Department
6	Distance From Home
7	Education
8	Education Field
9	Employee Count
10	Employee Number
11	Environment Satisfaction
12	Gender
13	Hourly Rate
14	Job Involvement
15	Job Level
16	Job Role
17	Job Satisfaction
18	Martial Status
19	Monthly Income
20	Monthly Rate
21	Number of Companies worked
22	Over18
23	Overtime
24	Percentage Salary Hike
25	Performance Rating
26	Relationship Satisfaction
27	Standard Hours
28	Stock Option Level
29	Total Working Years
30	Training time last year
31	Work life balance
32	Years at Company
33	Years in current role
34	Years since last promotion
35	Years with current manager

4.2. Number of Features obtained by Feature Selection Methods

Table 2 gives the number of features obtained by implementing the feature selection techniques like Correlation based Feature Selection (CFS), Information Gain (IG), Gain Ratio (GR), Chi-Square, and Fisher Exact Test. From the table 2, it is clear that the Chi-Square Feature Selection method gives a smaller number of features when comparing with other feature selection methods.

Table 2 Number of Features obtained by Feature Selection Methods

Feature Selection Method	Number of Features obtained
Original Dataset	34
Correlation based Feature Selection Method	32
Information Gain	29
Gain Ratio	27
Chi-Square	24
Fisher Exact Test	28

4.3. Performance Analysis of the Feature Selection Methods

The performance metrics like Classification Accuracy, True Positive Rate (TPR), Precision, False Positive, and Miss Rate are considered in this paper to evaluate the performance of the feature selection methods in the prediction of employee attrition in industry using different Machine Learning classifiers.

Table 3 gives the classification accuracy obtained by the feature selection methods using various classifiers. Table 4 depicts the True Positive Rate (in %) obtained by Feature Selection Methods using different classifiers. Table 5 presents the precision (in %) obtained by the feature selection methods using various classifiers. Table 6 depicts the False Positive Rate (in %) obtained by the feature selection methods using various classifiers. Table 7 gives the miss rate (in %) obtained by the feature selection methods using various classifiers.

Table 3 Classification accuracy (in %) obtained by Feature Selection Methods using different classifiers

Feature Selection Methods	Classification Accuracy (in %) by Classification Techniques					
	ANN	SVM	GBT	Bagging	RF	DT
Original Dataset	44.27	45.31	49.21	43.98	41.65	42.86
Correlation based FS	68.51	68.76	69.73	67.31	66.82	65.41
Information Gain	64.33	65.74	69.81	62.23	63.71	65.43
Gain Ratio	64.43	64.74	66.64	64.34	61.82	62.77
Chi-Square	89.44	85.75	89.15	79.81	80.53	81.22
Fisher's Exact	72.65	73.21	73.76	68.92	69.16	70.88

Table 4 True Positive Rate (in %) obtained by Feature Selection Methods using different classifiers

Feature Selection Methods	True Positive Rate (in %) by Classification Techniques					
	ANN	SVM	GBT	Bagging	RF	DT
Original Dataset	51.42	51.73	49.62	49.89	49.34	48.88
Correlation based FS	72.16	71.78	72.57	71.72	70.62	69.96
Information Gain	70.53	70.43	70.95	68.73	67.46	69.57
Gain Ratio	65.46	65.66	67.37	63.42	61.78	62.87
Chi-Square	88.54	87.72	89.22	86.34	85.62	81.11
Fisher's Exact	68.26	66.54	64.57	66.91	65.17	67.49

Table 5 Precision (in %) obtained by Feature Selection Methods using different classifiers

Feature Selection Methods	Precision (in %) by Classification Techniques					
	ANN	SVM	GBT	Bagging	RF	DT
Original Dataset	44.72	48.16	50.61	43.43	44.31	45.76
Correlation based FS	67.67	67.52	72.51	66.97	65.43	66.81
Information Gain	58.39	57.61	60.43	55.64	54.32	59.45
Gain Ratio	57.68	57.52	59.52	54.43	52.16	58.65
Chi-Square	83.18	85.24	85.42	81.53	79.72	78.18
Fisher's Exact	55.85	56.21	61.28	65.89	64.25	55.32

Table 6 False Positive Rate (in %) obtained by Feature Selection Methods using different classifiers

Feature Selection Methods	False Positive Rate (in %) by Classification Techniques					
	ANN	SVM	GBT	Bagging	RF	DT
Original Dataset	66.25	59.17	55.61	66.54	67.26	56.36
Correlation based FS	34.31	32.54	26.51	35.36	35.34	33.54
Information Gain	33.53	34.51	25.42	32.53	35.34	34.25
Gain Ratio	35.61	34.63	27.43	33.31	34.34	35.48
Chi-Square	7.62	7.84	6.73	10.25	17.33	20.09
Fisher's Exact	31.97	31.77	23.14	31.56	33.13	32.88

Table 7 Miss Rate (in %) obtained by Feature Selection Methods using different classifiers

Feature Selection Methods	Miss Rate (in %) by Classification Techniques					
	ANN	SVM	GBT	Bagging	RF	DT
Original Dataset	48.58	48.27	50.38	50.11	50.66	51.12
Correlation based FS	27.84	28.22	27.43	28.28	29.38	30.04
Information Gain	29.47	29.57	29.05	31.27	32.54	30.43
Gain Ratio	34.54	34.34	32.63	36.58	38.22	37.13
Chi-Square	11.46	12.28	10.78	13.66	14.38	18.89
Fisher's Exact	31.74	33.46	35.43	33.09	34.83	32.51

From the table 3, table 4, table 5, table 6 and table 7, it is clear that the Chi-Square Feature Selection with Gradient Boosting Tree (GBT) classifiers increased the classification accuracy, TPR, Precision, and also it reduced the error rates like FPR and Miss Rate for predicting the employee attrition in industry.

5. CONCLUSION

Employee attrition prediction has become a key issue in today's organisations. Employee attrition is a major problem for businesses, especially when trained, technical, and critical staff leave for better opportunities elsewhere. This leads in a financial loss as a trained employee must be replaced. Feature selection is critical in the pre-processing stage of data mining, and several data mining machine learning approaches struggle to manage vast volumes of irrelevant characteristics. Various feature selection strategies are used in this research article to improve the accuracy of employee attrition prediction in the industry. The performance of the different six classifiers, such as ANN, SVM, GBT, Bagging, RF, and DT, is tested for the prediction of employee attrition using Feature Selection approaches such as Information Gain, Gain Ratio, Chi-Square, Correlation based, Fisher's Exact. The Chi-Square Feature Selection with Gradient Boosting Tree classifier performs better in the prediction of employee attrition than other feature selection techniques with other classifiers, as evidenced by the results.

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